Related HOG Features for Human Detection Using Cascaded Adaboost and SVM Classifiers

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Abstract. Robust and fast human detection in static image is very important for real applications. Although different feature descriptors have been proposed for human detection, for HOG descriptor, how to select and combine more distinguish block-based HOGs, and how to simultaneously make use of the correlation and the local information of these selected HOGs still lack enough research and analysis. In this paper, we present a set of Related HOG (RHOG) features, including distinctive block-based HOGs (Ele-HOGs) which are selected by Adaboost and a global HOG descriptor which is concatenated by Ele-HOGs (CSele-HOG). Ele-HOG can discriminatively describe local distribution of human object while CSele-HOG contains global information. In addition, we propose a novel human detection framework of Cascaded Adaboost and SVM classifiers (CAS) based on RHOG features, which combines the advantages of Adaboost and SVM classifiers. Experimental results on INRIA dataset demonstrate the effectiveness of the proposed method.

Keywords: Machine Learning, Human Detection, Cascade, Adaboost, HOG.

1 Introduction

Human detection is an essential task in visual surveillance, image/video retrieval, and video annotation. However, detecting humans is a challenging problem for people's variable appearance, poses, clothes, illumination and complex background, especially in static image without motion information.

Machine-learning and sliding-window based human detection systems are presently the predominant methods [1, 5, 7]. In these approaches, each image is densely scanned from the top left to the bottom right with a rectangle sliding window in different scales. For each sliding window, certain features are extracted and sent to a classifier, which is trained offline on labeled training data [5]. It classifies the sliding window as human or nonhuman. For accurate human detection in real applications, the selection of feature descriptors and the classification algorithm are important factors.

Many feature descriptors have been proposed for human detection. Papageorgiou *et al.* [11] used Haar-like feature to describe different objects, such as faces, people

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and cars. This feature was proved to be less effective for human detection than for face detection. Then some other feature descriptors were proposed [1, 6, 9, 12], among which Histograms of Oriented Gradients (HOG) [1] is considered as one of the most successful human descriptor. In recent years, many variants of HOG [5, 16, 17, 19, 21] have been presented to improve performance of accuracy and speed. Besides edge and gradient feature, many researchers combined different kinds of features, e.g. Duan *et al.* [10] proposed Associated Pairing Comparison Features to combine color and gradient information. Ye *et al.* [3] designed a set of multi-scale orientation features which contains coarse and fine features. Combinations of HOG and Local Binary Pattern (LBP) feature were also proposed for human detection [5, 14, 15].

Although different feature descriptors have been proposed for human detection, for original HOG descriptor, how to select and combine more distinguishable block-based HOGs, and how to simultaneously make full use of the correlation and the local information of these selected HOGs lack enough research and analysis.

Besides the feature descriptor, the classifier also has great influence on the performance of human detection. The Support Vector Machine (SVM) and variants of boosted decision tree are two leading classifiers due to their good efficiency [5]. Oren *et al.* [8] firstly introduced machine-learning technology into human detection. They used SVM to train human detector, which was frequently adopted [1, 5, 18]. However, high dimensional features were needed for guaranteeing detection performance, which were time-consuming in sliding-window based detection system.

To improve processing speed, many approaches have been proposed [2, 4, 12, 19-22]. One of the most important methods was proposed by Viola *et al.* [4]. They used Haar-like features and Adaboost to train cascaded classifier for face detection. With the help of simple features, the integral image technology and the cascaded structure of classifier, this method achieved real-time speed with good detection performance. Inspired by [1] and [4], Zhu *et al.* [2] trained a cascaded classifier by AdaBoost based on variable-sized and block-based HOGs. Their cascaded classifier was proved to be dozens of times faster than the SVM classifier in [1]. In recent years, the idea of cascading different kinds of classifiers was also proposed to improve human detection performance [3, 14]. Zeng *et al.* [3] used mi-SVM (Support Vector Machine for multiple instance learning) to train the HOG and LBP feature respectively, and then cascaded the two mi-SVM classifiers directly. How to select and combine different kinds of classifiers and construct cascaded rejecters are important issues in designing human detection system for real applications.

In this paper, inspired by some present research [1, 2, 3, 5], based on 36 dimensional block-based HOGs [1, 2], we propose a feature selection and combination framework to retain discriminative local information and global information of human object. Besides, for real applications, we propose a method to cascade different kinds of classifiers to gain robust detection performance with fast speed. The main work in this paper is listed as following:

1). We present a set of Related HOG (RHOG) features including Elementary HOGs (Ele-HOGs) and Concatenation of Ele-HOGs (CSele-HOG). Ele-HOGs are discriminative block-based HOGs [1, 2] selected by AdaBoost, which describe local distribution of human object. CSele-HOG is a vector concatenated by Ele-HOGs, which contains global and correlative information.

2). Based on RHOG features, we propose a novel human detection scheme using Cascaded Adaboost and SVM classifiers (CAS). Firstly, Adaboost is used to select Ele-HOGs from a huge number of block-based HOGs. The first several stages of Adaboost are used as the first part of our CAS scheme. This part can reject most non-human candidates quickly. Secondly, Ele-HOGs are concatenated to be CSele-HOG descriptor and a SVM classifier is trained. This SVM classifier is used as the last part of our CAS scheme, which can guarantee a high detection performance.

3). When RHOG features are used in our CAS scheme, Ele-HOGs discriminatively describe the local information of human object while CSele-HOG describes the global information. So we simultaneously make use of the local and global information of each Ele-HOG. Moreover, it does not need extra time to calculate CSele-HOG because it is the by-product of computing Ele-HOGs. Experimental results on INRIA dataset show that using RHOG features in CAS framework achieves better detection performance compared with the state-of-the-art human detectors [1, 2].

2 Related Work

Dalal *et al.* [1] proposed HOG descriptor which is considered as one of the most successful features for human detection. In this approach, the 36 dimensional block-based HOG can effectively describe local information of human object. However, the extraction of HOGs is restricted to a single square scale (block with size of 16×16 pixels), so some distinctive HOG information within other variable scales or sizes may be omitted. Meanwhile, the HOG descriptor of each scanning window, which is constituted by 105 gradient histograms extracted from 7×15=105 blocks [1], may contain some redundancy information. Finally, the 3780 dimensional HOG descriptor is trained by SVM classifier, which is time-consuming in sliding-window based human detection system.

Zhu *et al.* [2] adopted Adaboost to select distinctive HOGs from a feature pool which is constructed by 5031 variable-sized and block-based HOGs. In this approach, many selected HOGs are big blocks which are not contained in the 105 fixed blocks in [1]. With the help of Adaboost and integral image techniques, this approach obtains faster speed with similar detection performance compared with [1]. However, this approach only uses block-based HOGs, which could well describe local distribution of human object but lost global information. Moreover, each weak classifier is based on 36 dimensional HOGs, which don't use the correlation information between different distinctive HOGs.

Ye *et al.* [3] proposed a two-stage classifiers scheme to combine coarse features and fine features. Adaboost is used to select coarse features in the first stage to guarantee high speed, and SVM is used to train fine features to gain high detection accuracy. In this method, the coarse features are the unit orientations while the fine features are the pixel orientation histograms of the unit. The fine feature had no relationship with the coarse feature.

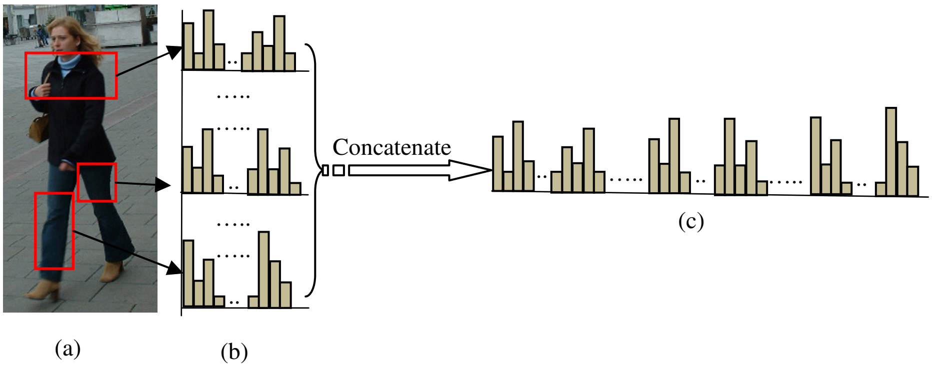

Fig. 1. Description of RHOG features. (a). some selected variable-sized blocks (b). some Ele-HOGs (c). construction of CSele-HOG descriptor.

3 Our Proposed Method

3.1 Related HOG Features (RHOG)

We propose a set of Related Histogram of Oriented Gradients (RHOG) features, which contains Elementary HOGs (Ele-HOGs) and the Concatenation of Ele-HOGs (CSele-HOG). Ele-HOG is a vector of block-based HOG with 36 dimensions [1,2] which are selected by Adaboost from a huge number of candidate HOGs, and CSele-HOG is a vector concatenated by Ele-HOGs.

Ele-HOG Feature. The construction method of Ele-HOG feature is similar to [1, 2]. Firstly, each detection window is divided into variable-sized blocks [2] and each block is divided into 4 cells; then the orientation over 0°~180° is divided into 9 bins. So each cell consists of a 9-bin Histogram of Oriented Gradients (HOG) and each block contains a concatenated 36 dimensional HOG feature; finally, all the block-based HOGs in the sliding window are used to constitute a feature pool, from which Adaboost is use to select Ele-HOGs, as shown in Figure 1 (b). In order to obtain Ele-HOGs quickly, we use integral images technology [4] and Convoluted Trilinear Interpolation (CTI) [5] to replace the trilinear interpolation in approach [1]. The improved Ele-HOG can train a fast cascaded rejecter by Adaboost.

CSele-HOG Descriptor. The CSele-HOG descriptor is concatenated by all Ele-HOGs selected by Adaboost as shown in Figure 1 (c). The dimension of CSele-HOG is decided by the number of Ele-HOGs, which can be calculated by the following equation:

$$D_{concatenation} = N^{*} D_{ele} \tag{1}$$

Where D_{ele} means the dimension of Ele-HOG, which is 36 in this paper. N denotes the number of Ele-HOGs selected by Adaboost. The value of N is decided by the number of stages of the cascaded rejecter. So we can select a proper number of cascaded stages to control the dimension of CSele-HOG descriptor.

Here, from a huge number of variable-sized and block-based HOGs, some discriminative ones are selected by Adaboost, which are called Ele-HOGs in this paper. These Ele-HOGs describe local distribution of human object discriminatively. In order to use the correlation of these distinctive Ele-HOGs, we concatenate them into a vector named CSele-HOG descriptor. Compared with Ele-HOGs, CSele-HOG descriptor contains discriminative global information, which can be used to train a SVM classifier with high detection performance.

CSele-HOG descriptor is concatenated by Ele-HOGs directly, and they have close relationship with each other. Therefore, we call them RHOG features. In the next section, RHOG features are used in Adaboost cascaded rejecter and SVM classifier of the CAS framework respectively, which can improve detection performance and processing speed at the same time.

3.2 Human Detection Scheme of Cascaded Adaboost and SVM Classifiers (CAS)

Based on RHOG features, we propose a novel human detection scheme of Cascaded Adaboost and SVM classifiers (CAS), aiming at achieving high detection performance and fast speed.

Training. We train the cascaded rejecter and SVM classifier on public data set INRIA [1]. The training data set of INRIA includes 2476 positive human patches (including left-right reflections) and 1218 negative non-human images.

Firstly, we use linear SVM to train weak classifiers of the cascaded rejecter and use Adaboost to select the discriminative weak classifiers to construct strong classifiers. The feature pool contains 2346 variable-sized HOGs, from which 5% HOGs are randomly sampled to train weak classifiers just as [2]. Here, we choose 1238 positive samples (the non-left-right ones) and 4000 negative samples randomly selected from the 1218 non-human images to construct training data set. The negative samples are updated in each round of strong classifier training process.

Secondly, we combine distinctive Ele-HOGs, selected by Adaboost, to construct CSele-HOG descriptor and use it to train SVM classifier with more discriminative global and correlation information. Inspired by [1], we use the above Adaboost cascaded rejecter to choose hard samples for CSele-HOG SVM classifier training. Figure 2 shows the details of the selection process of hard samples and the training process of CSele-HOG SVM classifier. First, as the red trace in Figure 2 shows, we use cascaded rejecter to detect the 2476 positive patches and choose the right detections as initial positive samples, while randomly detect the 1218 negative images and choose the wrong detections as initial negative samples. We use these initial hard samples to train the initial CSele-HOG SVM classifier. Then, as the blue trace in Figure 2 shows, we use the concatenated scheme of Adaboost cascaded rejecter and initial CSele-HOG SVM classifier to select more negative hard samples by exhaustively search false positives in the 1218 negative images. We combine the initial hard samples with the exhaustively searched hard samples to retrain the CSele-HOG SVM classifier to produce the final SVM classifier. The number of positive and negative samples used for the final SVM classifier training is decided by the cascaded rejecter and the scanning parameters of exhaustively searching which will be discussed in experimental section.

The size of all classifiers used in our experiment is 64×128 pixels. On the PC with 2.93 GHz CPU and 2GB memory, it takes several hours to train CSele-HOG SVM classifier, and several days to train cascaded rejecter by Adaboost. Each stage satisfies minimum detection rate of 0.999 and maximum false positive of 0.5.

Detecting. We use sliding-window technology to detect human object. For real-time applications, the ideal detection system should ensure the detection accuracy and at the same time have high detection speed. In this paper, we propose a novel human detection scheme of Cascaded Adaboost and SVM classifiers (CAS). Firstly we use the cascaded rejecter, which is trained by Adaboost based on Ele-HOG feature, to reject most non-human candidates quickly; then we use SVM classifier, which is based on CSele-HOG descriptor, to guarantee detection accuracy. The details are shown in Figure 3.

In the CAS scheme, we use Ele-HOGs and CSele-HOG descriptor in Adaboost cascaded rejecter and SVM classifier respectively. Ele-HOGs can be extracted very quickly and the cascaded rejecter can guarantee fast speed. CSele-HOG descriptor is concatenated by distinctive Ele-HOGs, so CSele-HOG SVM classifier can make sure high detection accuracy. Furthermore, we do not need to spend extra time to compute CSele-HOG descriptor because it is the by-product of selecting Ele-HOGs.

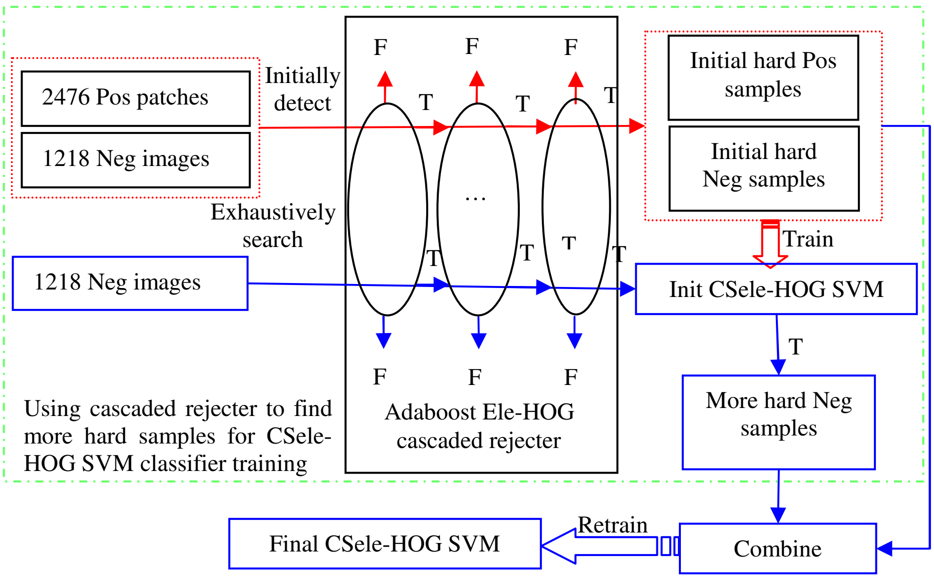

Fig. 2. The training process of the final SVM classifier based on CSele-HOG. (the red trace is the process of selecting initial hard positive and negative samples by using Adaboost, and then using them to train the initial CSele-HOG SVM classifier; the blue trace is the process of selecting more negative hard samples by using cascaded Adaboost and the initial CSele-HOG SVM classifier to exhaustively search the 1218 person-free images, and then combing them with the initial positive and negative hard samples to train the final CSele-HOG SVM classifier).

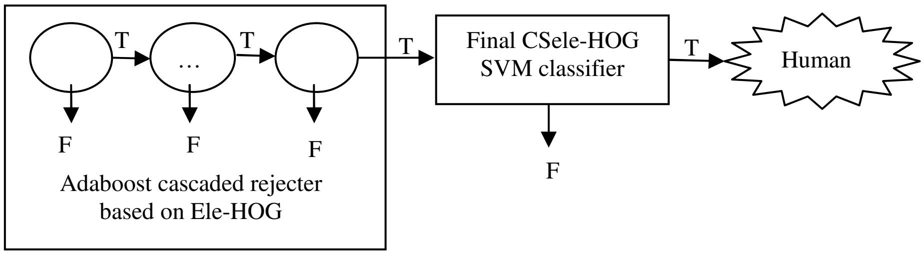

Fig. 3. Proposed human detection scheme based on Cascaded Adaboost and SVM classifier (CAS)

4 Experimental Results

4.1 Introduction of Experimental Condition

To quantitatively analyze classifier performance, we plot Detection Error Tradeoff (DET) curves on a log-log scale, i.e. miss rate (calculated in equation [2]) versus FPPW (false positives per window). Lower values are better. In the experiments, we use miss rate at 10^{-4} FPPW as a reference point for results analyzing.

$$miss\ rate = False\ Negatives\ /\ (True\ Positives + False\ Negatives) \tag{2}$$

The details of training process are described in section 3.2. In our experiments, the test data set comes from INRIA dataset [1], including 1106 human patches with 64×128 pixels and 453 non-human images with variable sizes from 320×240 to 648×748 pixels. We obtain miss rate by using classifiers to detect the 1106 human patches, and get FPPW by using classifiers to scan the 453 non-human images with the scanning parameters as following: scale = 1.12 and stride = (8, 8). The total number of non-human patches is 3,150,775.

4.2 Experimental Results and Analysis

For fair comparison, we train an HOG SVM classifier using approach [1]. The only difference is that we use integral images [4] and the Convoluted Trilinear Interpolation (CTI) [5] to replace the trilinear interpolation in [1]. Results show our HOG SVM classifier is *5* times faster than the one provided in OpenCV [1], with similar detection accuracy. In the following experiment, we will compare our method with this improved HOG SVM classifier.

We design three sets of experiments to evaluate our approach. 1) We validate the effectiveness of CSele-HOG descriptor by comparing CSele-HOG SVM classifier with HOG SVM classifier and Zhu's HOG cascade-of-rejecters [2]. 2) We evaluate the performance of our RHOG-based human detection scheme CAS by comparing CAS scheme with the scheme which only uses CSele-HOG SVM classifier. 3) We evaluate RHOG features by comparing the combination of Ele-HOG cascaded rejecter and CSele-HOG SVM classifier with that of Ele-HOG cascaded rejecter and HOG SVM classifier.

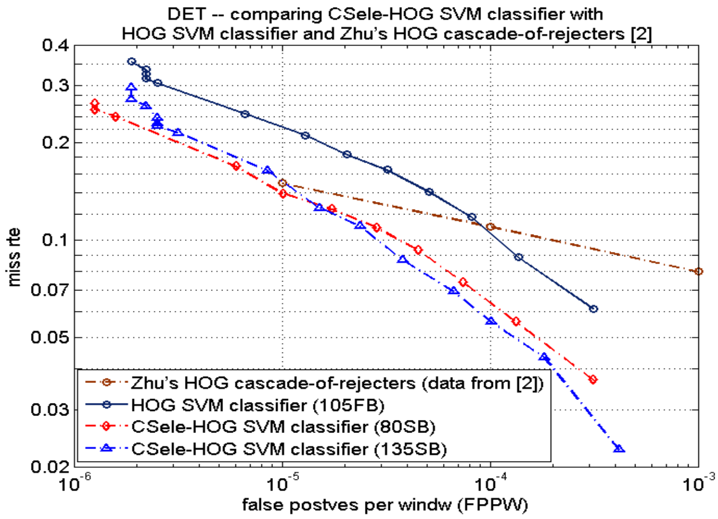

Fig. 4. Comparison of CSele-HOG SVM with HOG SVM [1] and Zhu's [2]

CSele-HOG Feature. To compare with HOG descriptor [1], which is extracted from 105 fixed blocks (105FB), we use Adaboost to select similar number of Ele-HOGs to construct CSele-HOG descriptor. As section 3.2 discribes, in our experiment, the number of Ele-HOGs selected by the first 4 and 5 stages of the cascaded rejecter is 80 and 135 respectively. We construct two CSele-HOG descriptors by 80 selected Ele-HOGs and 135 selected Ele-HOGs, and train two SVM classifiers – CSele-HOG SVM (80SB) and CSele-HOG SVM (135SB).

We compare CSele-HOG SVM with HOG SVM and Zhu's HOG cascade-of-rejecter to validating the effectiveness of the proposed CSele-HOG descriptor. The result is shown in Figure 4, among which the data of Zhu's method comes from [2].

Compared with "HOG SVM (105FB)" at 10^{-4} FPPW, our "CSele-HOG SVM (80SB)" and "CSele-HOG SVM (135SB)" improve performance by 4.5% and 5% respectively. Even using fewer blocks, our "CSele-HOG SVM (80SB)" is more discriminative. The reason is that CSele-HOG descriptor is concatenated by distinctive Ele-HOGs which are selected by Adaboost from a huge number of variable-sized and block-based HOGs. However, HOG descriptor is combined by unselected fixed block-based HOGs which may contain several indistinctive ones while miss some distinctive ones of other sized blocks.

Compared with Zhu's method [2], our CSele-HOG SVM also gain better performance at 10^{-4} FPPW. Though [2] use Adaboost to select distinctive HOGs (Ele-HOGs), these features only contain local information and ignore the correlation of these features.

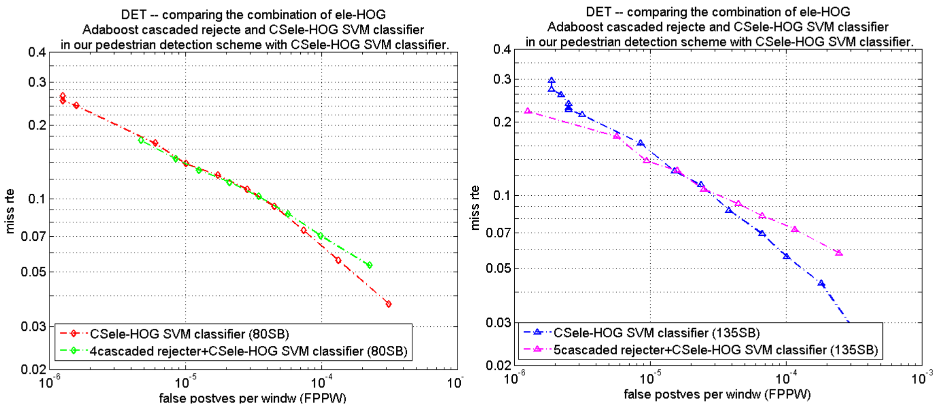

Fig. 5. Results of CSele-HOG SVM and CAS with "cascaded rejecter+CSele-HOG SVM"

CAS Scheme. We test our human detection scheme by comparing CAS scheme which consists of the first 4 stages of Ele-HOG cascaded rejecter and CSele-HOG SVM (80SB) with a scheme which only uses CSele-HOG SVM (80SB), and comparing the CAS scheme that consists of the first 5 stages of Ele-HOG cascaded rejecter and CSele-HOG SVM (135SB) with a scheme that only uses CSele-HOG SVM (135SB).

As Figure 5 illustrates, the detection performance at 10^{-4} FPPW decreases a little by adding 4 or 5 stages of cascaded rejecter before SVM classifier both in the two sets of comparisons,. The reason is probably that cascaded rejecter rejects some true positives which will not be rejected by the SVM. Meanwhile, at lower FPPW, the detection performance declines fewer and even increases, because the cascaded rejecter and the SVM classifier may be complementary, resulting in less false positives. Moreover, the detection speed gets faster because cascaded rejecter can reject most non-human candidates at the first several stages quickly, e. g. the first 4

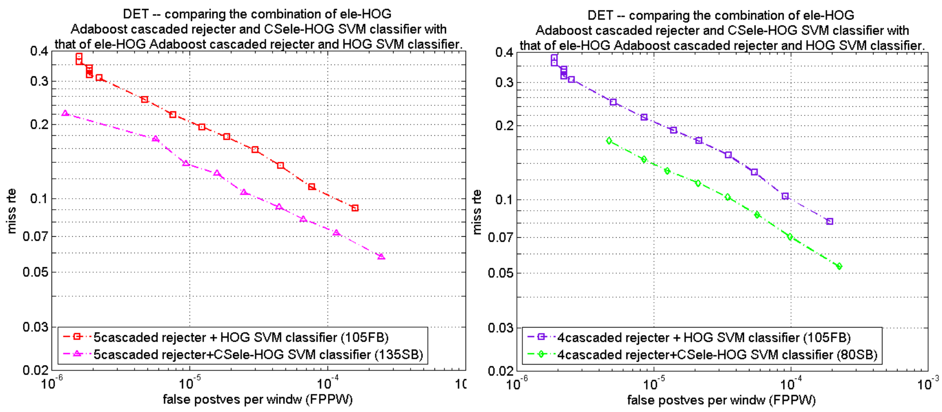

Fig. 6. Comparisons of "cascaded rejecter + CSele-HOG SVM" with "cascaded rejecter + HOG SVM"

stages can reject more than 90 percent of detection windows. Consequently, by adding several stages of cascaded rejecter before SVM classifier, we combine the advantages of Adaboost and SVM methods, achieving faster speed without sacrificing detection performance.

RHOG Features in Our CAS Scheme. We test the performance of RHOG features, by comparing the combination of Ele-HOG cascaded rejecter and CSele-HOG SVM ("cascaded rejecter + CSele-HOG SVM") with that of Ele-HOG cascaded rejecter and HOG SVM ("cascaded rejecter + HOG SVM") in CAS scheme.

In the two sets of experiments shown in Figure 6, compared with "cascaded rejecter + HOG SVM", "cascaded rejecter + CSele-HOG SVM" method improves the detection performance by about 3% at 10^{-4} FPPW while achieves a faster speed. The main reason for the higher performance is that CSele-HOG descriptor is more discriminative than HOG descriptor. The main reason for the faster speed is that as the by-product of selecting Ele-HOGs, CSele-HOG descriptor does not cost extra computing time. Some results of "4cascaded rejecter + CSele-HOG SVM(80SB)" are shown in Figure 7.

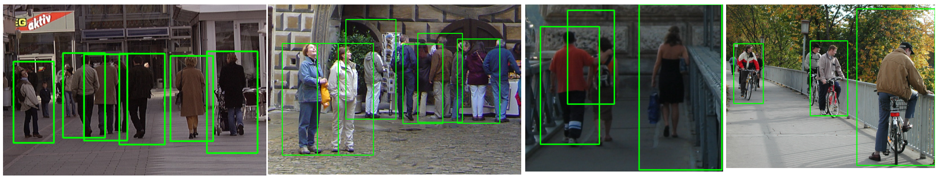

Fig. 7. Some results of our "4 cascaded rejecter + CSele-HOG SVM (80SB)" on INRIA

5 Conclusion

In this paper, we present a set of Related HOG features to describe distinctive local and global information of human object, including Ele-HOGs and a CSele-HOG descriptor. Meanwhile, we propose a novel human detection scheme of Cascaded Adaboost and SVM classifiers (CAS) to combine advantages of Adaboost and SVM. The experimental results show that CSele-HOG descriptor is more discriminative than original HOG descriptor [1]. Moreover, using RHOG features in our CAS scheme can achieve robust and fast detection performance. The Ele-HOG based cascaded rejecter in the proposed CAS scheme can reject most non-human candidates very quickly while the CSele-HOG based SVM classifier can obtain high detection performance.

In the future, we want to combine other features, such as LBP, in our scheme and try to extend the proposed method to handle variations in views. In addition, we will evaluate the proposed method on more public data sets.

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